

# Corporate Governance and Pollution Externalities of Public and Private Firms\*

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The number of U.S. publicly traded firms has halved in 20 years. How will this shift in ownership structure affect the economy's externalities? Using comprehensive data on greenhouse gas emissions from 2007 to 2016, we find that independent private firms are less likely to pollute and incur EPA penalties than are public firms, and we find no differences between private sponsor-backed firms and public firms, controlling for industry, time, location, and a host of firm characteristics. Within public firms, we find a negative association between emissions and mutual fund ownership and board size, suggesting that increased oversight may decrease externalities. (*JEL* G23, G32, G34, G38, L33, P18, Q53, Q54)

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As human activity tilts the global environmental balance, governments have come under pressure to coordinate, regulate, and monitor to reduce its effects. The recent withdrawal of the United States, the second largest global emitter of greenhouse gases, from the Paris Climate Accord, however, has shown that much of the burden of curtailing pollution may rest on the millions of daily decisions of concerned people and firms. Can we expect costly prosocial actions from firms and their investors? Friedman (1970) argues that firms should focus on maximizing profits for shareholders, who can privately donate their wealth to causes of their choosing. Thus, Friedman prescribes that firms should refrain from unprofitable prosocial behavior regardless of their ownership structure.

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As Baron (2007), Benabou and Tirole (2010), and Hart and Zingales (2017) point out, however, Friedman's argument breaks down when investors incur frictions to reverse harmful choices of firms or when firms have a comparative advantage in creating prosocial outcomes. The existence of these frictions and advantages is plausible. For example, the cost of neutralizing a given pollutant might exceed the benefits derived from emitting it.

In the small theoretical literature that has emerged to study prosocial behavior by firms, the optimal extent of this behavior depends on assumptions about organizational structure and the resultant incentives of investors and managers, as well as whether prosocial behavior benefits the firm long term. In theory and in practice, there are many reasons to think that the equilibrium level of prosocial behavior of publicly and privately held firms may be different. On one hand, investors evaluate public companies quarterly, potentially encouraging managers of public firms to sacrifice long-term value for more observable short-term results. Hart and Zingales (2017) propose a model in which investors' preferences include environmental concerns. Their model predicts that public firms, with their diffuse ownership and resultant low level of personal responsibility felt by each voting investor, will incur an "amoral drift," whereas closely held private firms will more often make prosocial decisions. In possible support of this hypothesis, Bernstein and Sheen (2016) find that health records of restaurants improve when they are taken over by private equity owners, and Cohn, Nestoriak, and Wardlaw (2018) find that workplace safety improves. These simply may be profit-maximizing decisions, however.

On the other hand, private owners may have clearer incentives to focus exclusively on profits. Individual business owners may have no other sources of wealth. Private equity sponsors and the managers they hire are highly motivated to maximize financial returns due to the strong alignment of their incentive structure with the firm's exit value. Perhaps as a result, controversy surrounds the question of whether private equity buyouts have negative externalities like reducing employment (Davis et al. 2014). Furthermore, some private firms may benefit from the relatively limited distribution of their financial statements. Public firm financial statements must disclose potentially reputation-damaging events, such as material Environmental Protection Agency (EPA) fines. Thus, that we should expect more prosocial behavior from private firms is not immediately obvious. This question assumes increased importance as the structure of the U.S. economy changes. Doidge, Karolyi, and Stulz (2017) identify fewer public firms today than there were 40 years ago, whereas the total number of firms has held steady, implying a larger and growing proportion of private firms in the U.S. economy.<sup>1</sup>

<sup>1</sup> An active recent literature investigates other differences between public and private firms such as their differential access to capital (Brav 2009; Michaely and Roberts 2012; Gao et al. 2013) and how these differences affect their ability to innovate (Bernstein 2005; Acharya and Xu 2017) or invest in new opportunities (Mortal and Reisel 2013; Asker et al. 2015; Gilge and Taillard 2016; Phillips and Sertsios 2016). Our paper expands this literature into the area of governance and incentives.

We focus on greenhouse gas emissions as a measure of prosocial choices because the potential harm is widely shared and may only be minimally borne by the polluter. Greenhouse gas emissions have featured in a handful of past and contemporaneous studies in economics and finance. For example, Ilhan, Sautner, and Vilkov (2019) show that S&P 500 firms that emit more have higher left tail risk, as measured from options and higher analyst uncertainty about firm fundamentals. Krueger, Sautner, and Starks (forthcoming), in a survey of institutional investors, reveal that many believe that climate risks from emissions of greenhouse gases have already begun to materialize. Many also believe that engagement, rather than divestment, is an appropriate way to address climate risks.<sup>2</sup>

Importantly for this study, Fowlie (2010) shows that, for utilities, reducing greenhouse gas emissions is costly and therefore not clearly a profit-boosting decision. A recent *Wall Street Journal* analysis suggests that the same is true for airlines (McCartney 2019). However, our lack of data on the cost structures of other industries leaves open the possibility that findings of differences in emissions between public and private firms can be partially ascribed to one or the other structures being more conducive to making cost-saving, profit-maximizing decisions.

Our data source is the detailed documentation that the EPA provides on permits and emission levels of its regulated facilities and on its enforcement actions against some of these facilities. We hand-match this facility-level data to firm-level accounting data from Capital IQ. For each linked firm, we use the SEC's EDGAR Web site along with news articles and company Web sites to look up the history of its public or private status during each year of 2007–2016, the period when Capital IQ financial data are available. We record in each year whether a private firm is sponsor backed or whether it is independently run.

With these data, we test whether private or public EPA-regulated firms have a greater propensity to emit greenhouse gases and whether any firm characteristics mitigate this effect. We examine both raw emissions and emissions scaled by revenue, and control variables include total assets, leverage, and the proportion of property, plant and equipment in total assets, as well as state, year, and 4-digit SIC code fixed effects. Using data from the two EPA databases that report greenhouse gas emissions, we find that private independent firms emit less than do comparable public firms, whereas there is no strong difference between sponsor-backed private firms and public firms. The effect is economically significant, with independent private firms emitting roughly one-third of a standard deviation less CO<sub>2</sub> equivalent greenhouse gases than do

<sup>2</sup> Our paper is also related to the growing literature on corporate social responsibility (CSR). This literature has focused on large public firms and generally on the question of whether CSR activities generate increased earnings or returns (Heinkel, Kraus, and Zechner 2001; Hong and Kacperczyk 2009; Ferrell, Liang, and Renneboog 2016 Lins et al. 2017). Starks, Venkat, and Zhu (2017) find that long-term investors have a preference for high-CSR firms.

public firms. The result survives when we match each private firm to a similar public firm and when we divide emissions by the SIC-code average in that year.

As total revenues can be a rough measure of output, we obtain electricity generation data for a subset of utilities at the generator level. When emissions are scaled by generation, we find similar results. That weighted average generator age does not fully explain the results suggests that the age of the production assets—even if it were entirely exogenously determined by younger firms being more likely to be private—does not drive the result.

Next, we test whether public or private firms are more likely to run afoul of EPA regulations. While Friedman did not advocate breaking the law in order to enhance shareholder value, he would endorse coming as close as possible to the legal limits, a policy which, if implemented imperfectly, risks more fines and regulatory actions. We find that independent private firms are less likely to incur actions and penalties than are public firms. This result is weaker in the smaller sample of matched firms and with the process of adjusting for industry averages.

It is possible that firms' listing decisions are correlated with their decisions about how much to pollute. Following prior literature, we address this possibility by estimating the probability of being a private independent and private sponsored firm, like in Acharya and Xu (2017), and control for the inverse Mills ratios in our regressions. The Online Appendix presents our results, which remain unchanged.

Next, we investigate potential causes of our findings using a subsample of public firms for which we have rich data on investor holdings and governance characteristics, with the caveat that the results we find will only be indicative in terms of the differences between public and private firms. First, we test whether measures of disclosure and personal responsibility, proxied by concentrated decision-making power, are related to differences in pollution choices across public firms. We find a positive effect of required disclosure among private firms, and no effect of firm age (as a proxy for reputation). We do find that firms emit less when they have higher mutual fund ownership and larger boards. This suggests that the presence of concerned oversight, either at the investor level or at the firm level, could be a driver of reduced emissions.

Next, we construct proxies for short-term investor pressure to perform. We find that the earnings response coefficient (as measured by the SUE decile) is positively related to emissions, suggesting that short-term pressure is indeed important. However, the presence of a golden parachute at the firm is also positively associated to emissions, which adds nuance to this result and suggests that that CEO job security, in particular, is not driving it. The presence of a staggered board or a poison pill are not associated with emissions among public firms. On the whole, these results provide partial evidence that governance by concerned investors could be at play in a firm's decision to pollute.

## 1. Data

### 1.1 Public and private firm data

Firm financial data are from Capital IQ, which is also used by Gao, Harford, and Li (2013), Phillips and Sertsios (2016), and Acharya and Xu (2017) in their studies of public and private firms. We download time-series financial data for 13,393 U.S. firms and subsidiaries from 2007 to 2016. Of these entities, 10,957 have more than 1 year of data with total assets, total debt and total revenue defined. Capital IQ often obtains its data from publicly available financial statements, so our private firm data oversamples larger private firms and those that issue publicly traded debt that involves SEC disclosure requirements. It is possible that our results may not apply to the more opaque private firms that are not in our data. Later, we investigate whether 10-K disclosure requirements among private firms in our sample are related to emissions levels, which should partially address this concern. Lastly, results may not apply to non-U.S. settings, where different managerial incentives may be present. Facilities of U.S. businesses abroad are subject to home country pollution requirements and are also not in our data. Ben-David, Kleimeier, and Viehs (2018) find that firms have incentives to “export” their polluting activities to countries with less-stringent pollution regulations.

We obtain the full name history of EPA facilities, and the dates associated with each name via a Freedom of Information Act request. For each Capital IQ firm, we search the data set of EPA facilities for matches by name. Online Appendix A describes the full hand-matching process. We find that 2,345 firms in the Capital IQ database have matching facilities in the EPA database during a time period that overlaps with that of data availability in Capital IQ.

Capital IQ provides a variable indicating whether the firm is public or private, but it is not a time-series variable, and it labels subsidiaries of public firms, government-owned entities, religious institutions, etc., as private. Thus, for each Capital IQ entity that has one or more facilities in the EPA data, we search the SEC’s EDGAR Web site for the private, public or subsidiary status for the firm in each year since 2007. For firms that file a 10-K, item number 5 provides information on whether the stock is publicly traded and on which exchange it is listed. We consider a stock publicly traded if it trades via Pink Sheets or over-the-counter, but, to avoid gray areas, we remove firms that trade and yet do not file a 10-K in a given year (stocks that trade via Pink Sheets are not required to). If the firm is private, we determine whether the firm is owned by a private equity sponsor or is independent from company Web sites or news searches using Google or Factiva. We also remove the handful of municipally owned entities from the sample.

We delete any firm with assets or revenues below \$1M, but using a cutoff of \$10M or \$100M does not materially change the results. In the firm-level analysis, we also remove conglomerates that do not easily fit into one industry; for example, Berkshire Hathaway not only sells Fruit of the Loom underwear

but also has energy subsidiaries, and thus there is no reasonable SIC code at the firm level. We can retain them in facility-level analyses, because we have facility-level SIC codes. Figure 2 presents the number of firms in each year classified by public or private status. In the full sample, approximately 7.4% of our firms are private: 5.4% are private independent firms, and 2% are private sponsor-backed firms. In the subsample that has carbon emissions data described in the next section, 10.7% of firms are private, with 8.4% being private independent firms and 2.3% being sponsor backed. While more than 7% of firms are private prior to 2014, Capital IQ data are missing for some of the private firms in later years, resulting in their being only 7%, 5.8%, and 5% of private firms in 2014, 2015, and 2016. In untabulated regressions, we find that dropping these years does not affect the nature of the results. A related point is that the number of public firms in our data set is not decreasing over the years like it is in the broader Compustat data. This is because there is a slightly better coverage and therefore a better match rate between EPA data and Capital IQ data in the later years of the sample period (e.g., 1-800-Flowers exists in Capital IQ from the inception of the data set, but is only in the EPA data starting in 2015), and because the firms in our matched sample of Capital IQ and EPA firms are not the smaller firms that are dropping out of Compustat as documented by Doidge, Karolyi, and Stulz (2017). This may result in our having fewer private firms in our sample than we would like.

The public firms in our sample have relatively uniform governance structures due to regulation, though we do include firms issuing publicly tradable units, which are common in the energy sector. In contrast, private firms have more leeway to adapt their structures and governance to the needs of their owners. As a result, beyond being more closely held, the private firms in our sample have a spectrum of organizational structures. Example of private firms in our sample are a private equity portfolio company like Avaya, Inc., or Tesla, Inc., prior to its initial public offering (IPO) in 2010. Another structure is that of Golden Grain Energy, for which private units are tradable on an online matching system available on the company's Web site, and in practice is held by farmers. Still others, for example Ace Hardware, are owned by their customers. Although we can separate out sponsor-backed firms, distinguishing between the other types of private firm is beyond the limits of our data set. While their structures vary, the private firms in our sample have in common that their owners are more involved in the management of the firm than are transient atomistic investors of public firms.

Public and private energy firms, in particular, have corporate structures that are rare outside of the energy sector. Among public energy firms, master limited partnerships, which issue units instead of shares, are common alternatives or complements to a common stock structure. These structures are only legal in the energy industry and in real estate. Units have limited voting rights. In cases in which an MLP is partially owned by a parent public company, effectively giving investors a choice of whether to invest in tax advantaged

units or in common stock, we allocate the facilities to this traditionally structured parent. Among private energy firms, the most common structure is the cooperative, which is owned by its customers. Cooperatives return profits to shareholders in proportion to their energy usage and not in proportion to their ownership percentage. In this sense they purport to be nonprofit, but none of the cooperatives we identified reported zero EBIT in Capital IQ. Also, energy prices and thus revenues to these firms are often regulated. Conclusions drawn from our study are influenced by characteristics of this sector, which is the heaviest producer of greenhouse gases and thus crucial in the study of climate change, but may have more limited application to corporate externalities that are unrelated to air pollution.

We use several firm-level financial variables from Capital IQ which we describe in Table 1. Table 2 presents summary statistics of the current firm-level sample, and Table C1 of the Online Appendix presents summary statistics on the facility-level sample. These tables also present the results of *t*-tests comparing private independent firms to public firms in Column 3 and private sponsor-backed firms in Column 5. Total assets average \$9,685M for public firms and \$12,890M for private independent firms, and this difference is significant at the 5% level. Total assets for sponsor-backed firms averages \$3,910M and this difference is significantly different from the public firm average at the 1% level. Figure 1 shows that though the means are different, the distributions of firm sizes for public and private firms in our sample are visually similar. In untabulated results, the study's findings are similar if we remove all public firms that are larger than the largest private firm. The average of total revenues is higher for public firms, at \$6,543M compared to \$3,321M and \$2,187M for private independent and private sponsor-backed firms. The private independent firms in our sample tend to be more asset intensive than the public firms or the private sponsor-backed firms with ratios of PP&E to assets averaging 0.39 versus 0.30 for public and private sponsor-backed firms.

## 1.2 Emission and enforcement data

Pollution data are from the EPA's Enforcement and Compliance History Online (ECHO).<sup>3</sup> Data sets include environmental permit, inspection, violation, enforcement action, and penalty information on EPA-regulated facilities. The following sections describe the emissions, violation, and other data that we use in this study.

**1.2.1 Greenhouse gas emissions.** We focus on air emissions because the detrimental effects, and therefore permit limits, of the release of chemicals into water and earth depend strongly on the location of release. For example, the release of a toxic chemical into a large body of water can be less harmful

<sup>3</sup> <https://echo.epa.gov/tools/data-downloads>

**Table 1**  
**Variable descriptions**

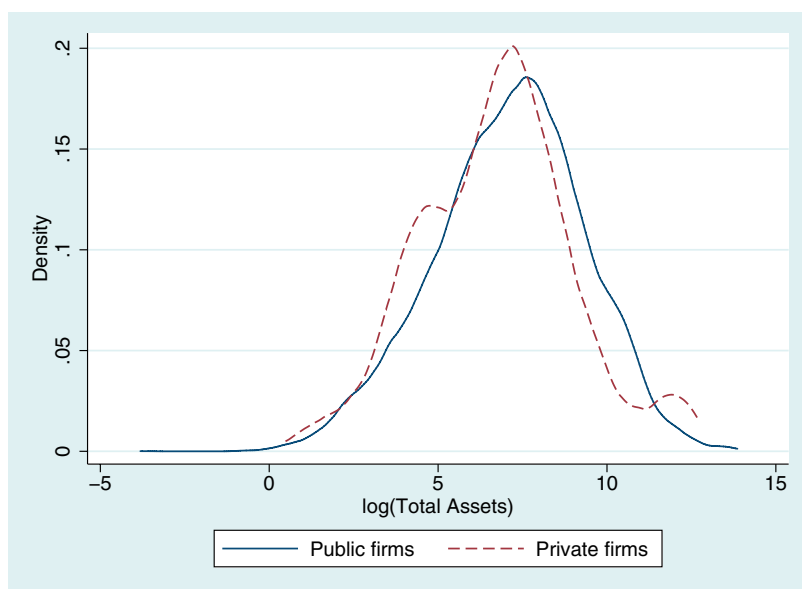
Variable	Description	Source
Private	An indicator variable for a firm that is not publicly traded in a given year. We define publicly traded firms as firms with equity ownership that trades on an exchange and that file 10-Ks with the SEC. We remove firms that are listed but do not file 10-Ks with the SEC	EDGAR, company Web sites, news
PrivateIndependent	Indicator variable for firms with equity ownership that is not traded on an exchange or controlled by a private equity firm.	SEC Edgar, company Web sites, news
PrivateSponsor	Indicator variable for firms with equity ownership that is not traded on an exchange and that is controlled by a private equity firm.	SEC Edgar, company Web sites, news
CO2eG	CO <sub>2</sub> -equivalent emissions of carbon dioxide, methane, nitrous oxide and fluorinated greenhouse gasses, in millions of metric tons. The Greenhouse Gas Reporting Program includes data since 2010	EPA
CO2C	Pounds of carbon dioxide emissions as measured by the Clean Air Markets Division (CAMD)	EPA
NOC	Pounds of nitrogen oxide emissions as measured by the Clean Air Markets Division (CAMD). These are in CO <sub>2</sub> equivalent	EPA
SO2C	Pounds of sulphur dioxide emissions as measured by the Clean Air Markets Division (CAMD). These are in CO <sub>2</sub> equivalent	EPA
CO2e	Combined variable that is CO <sub>2</sub> C + NOC + SO <sub>2</sub> C when these exist, and CO <sub>2</sub> eG otherwise. We prioritize CAMD data because it is of the highest quality according to the EPA Web site, but prioritizing the GHGRP data does not affect our results	EPA
NetGeneration	Net generation in megawatt hours (presented in millions of MWH in the summary statistics) aggregated from the generator level _GEN signifies that a variable is scaled by this variable	EIA
Plant_age	Plant age computed by weighting generator ages by output	EIA
numAIF	The total number informal administrative actions against that facility or firm in a given year	EPA
numAFR	The total number formal administrative actions against that facility or firm in a given year	EPA
numAFR	The total number of judicial actions against that facility or firm in a given year. Judicial actions are resolved by the courts outside the EPA	EPA
TotalPenalty	Total EPA penalty in thousands of dollars for a given facility or firm year	EPA
TotalRevenue	Annual total revenue. _R signifies that a variable is scaled by TotalRevenue	Capital IQ
DA	The ratio of total debt to total assets	Capital IQ
TotalAssets	The total assets of the firm	Capital IQ
NetPPEA	Net property, plant and equipment scaled by total assets	Capital IQ
Edgar10K	Indicator variable for whether the firm files a 10K in the given year	SEC EDGAR
CountGreenhouseGas	The count of the number of times that the word “greenhouse gas” appears in the 10-K	SEC Edgar
ERC_suedecile	Earnings response coefficient: The coefficient on the regression of returns on the announcement date on the earnings surprise (SUE) score	IBES and CRSP
GParachute	An indicator for a golden parachute	IRRC governance
CBoard	An indicator for a classified board	IRRC governance
ActiveMFown	Mutual fund ownership: sum of shares owned by all mutual funds divided by shares outstanding, and capped at 1, minus the shares owned by passive funds	CRSP mutual fund database
PassiveMFown	Mutual fund ownership by passive funds: Funds with any index fund type flag in CRSP plus ETFs, but not ETNs	CRSP mutual fund database
Boardsize	The size of the board.	IRRC Directors
Age	Firm age based on firm’s founding date or IPO date if the former does not exist	Jay Ritter’s Web site

Table 2  
Firm-level summary statistics

	(1) Public Mean	(2) p50	(3) Private independent Mean	(4) p50	(5) Private sponsor Mean	(6) p50	(7) SD	(8) N
CO2eG	4.310	0.320	2.499*	0.174	5.412	0.151	12.26	2,579
CO2C	17.82	5.693	5.048***	1.176	13.52	1.092	25.23	732
NOC	0.0154	0.00363	0.00598***	0.000523	0.00781*	0.000189	0.0240	736
SO2C	0.0423	0.00625	0.0100***	0.00257	0.0418	2.10e-05	0.0821	689
CO2e	5.635	0.393	2.867**	0.195	6.437	0.217	15.06	2,794
logCO2eG	0.773	0.275	0.667	0.160	0.700	0.140	1.042	2,583
logCO2C	1.272	1.739	0.371**	0.162	0.490*	0.0878	2.370	732
logNOC	-6.098	-5.618	-6.883***	-7.556	-7.570***	-8.574	2.603	736
logSO2C	-6.399	-5.075	-7.853***	-5.964	-8.536***	-10.77	4.099	689
logCO2e	-0.717	-0.932	-1.055***	-1.633	-0.987	-1.527	2.329	2,797
CO2eG_R	0.000929	0.000113	0.00216***	0.000688	0.00178	0.000291	0.00437	2,579
CO2C_R	0.00323	0.00193	0.00452	0.00152	0.00327	0.000592	0.00739	732
NOC_R	2.82e-06	1.26e-06	5.33e-06***	1.74e-06	1.77e-06	1.05e-07	5.48e-06	736
SO2C_R	6.29e-06	2.45e-06	9.73e-06***	3.56e-06	6.74e-06	1.13e-08	1.10e-05	689
CO2e_R	0.00114	0.000130	0.00257***	0.000716	0.00182	0.000320	0.00475	2,794
logCO2eG_R	-9.148	-9.084	-7.409***	-7.283	-8.050***	-8.141	2.287	2,579
logCO2C_R	-7.252	-6.248	-6.398***	-6.491	-7.062	-7.431	2.302	732
logNOC_R	-14.62	-13.59	-13.60***	-13.26	-15.12	-16.07	2.635	736
logSO2C_R	-14.98	-12.92	-14.61	-12.55	-16.21	-18.30	4.188	689
logCO2e_R	-8.981	-8.947	-7.304***	-7.242	-8.018***	-8.047	2.357	2,794
CO2e_GEN	875.09	901.38	869.18	839.67	737.91**	618.34	308.53	738
logCO2e_GEN	6.71	6.800	6.725	6.733	6.513***	6.699	0.402	738
NetGeneration (M)	21.39	7.430	4.72***	1.076	15.10	1.678	28.34	738
PlantAge	26.69	28.39	24.01*	24.71	15.56***	13.78	12.34	723
numAFR	0.409	0	0.126***	0	0.306	0	2.229	15,543
numJDC	0.0352	0	0.00368	0	0.00759	0	1.025	15,543
TotalPenalty	1.151	0	3.657	0	310.3	0	46,906	15,543
TotalRevenue	6,543	1,131	3,321***	521.5	2,187***	1,069	21,417	15,543
lagDA	0.261	0.224	0.416***	0.367	0.601***	0.539	0.319	15,543
lagAssets	9,685	1,292	12,890**	686.5	3,910***	1,211	40,986	15,543
lagNetPPEA	0.298	0.217	0.392***	0.338	0.295	0.196	0.253	15,543
Edgar10K	1.001	1	0.361***	0	0.489***	0	0.223	15,543
Panel B								
	(1) Mean	(2) p50	(3) SD	(4) N				
Age	32.83	23	30.26	925				
CountGreenhouseGas	7.675	3	12.47	2,340				
Maxinstown	0.0913	0.0760	0.0801	2,362				
ActiveMFown	0.159	0.150	0.0983	2,328				
PassiveMFown	0.102	0.102	0.0544	2,328				
Boardsize	10.50	10	2.018	1,509				
ERC_suedecile	0.00802	0.00674	0.00989	2,355				
GParachute	0.831	1	0.375	1,564				
CBoard	0.324	0	0.468	1,564				

Firm-level summary statistics. Table 1 defines the variables. Panel A presents statistics for variables for public and private firms, and panel B presents summary statistics for variables for public firms. In *t*-tests for differences with public firms, \**p* < .1; \*\**p* < .05; \*\*\**p* < .01.

than release of the same amount of the chemical into a stream that is home to a protected species, and permit limits vary accordingly. The EPA measures and collects air emissions data under four programs: the Greenhouse Gas Reporting Program (GHGRP), the Clean Air Markets Division (CAMD), the National Emissions Inventory (NEI), and the Toxics Release Inventory (TRI).



**Figure 1**  
Kernel densities of size for public and private firms

The GHGRP collects greenhouse gas<sup>4</sup> emissions data from larger facilities since 2010. These emissions are converted into metric tons of carbon dioxide equivalent to standardize their potency in causing global warming.<sup>5</sup> The program covers 8,000 large emitters. Table 1 contains variable definitions, and Table 2 summarizes these data in millions of metric tons of CO<sub>2</sub>e. The data are available from 2010 to 2016, and we call this variable *CO2eG*.

The second source of emissions data we use is the Clean Air Markets programs data. These data are for the largest emitters and measure emissions of fine particles, ozone, sulfur dioxide (SO<sub>2</sub>), nitrogen oxides (NO<sub>x</sub>), mercury, and other significant air pollutants. Most of the reported emissions from these programs are from hourly sampling performed by Continuous Emission Monitoring Systems (CEMS) and are generally considered the highest quality air emissions data according to the EPA's Web site. The data include over 1,300 facilities covered under the Acid Rain Program and Clean Air Interstate Rule. The data are available from 2007 to 2015: as of this writing, the EPA had not included the 2016 data on the central download Web site. However, we find the

<sup>4</sup> These are sulfurhexafluoride, perfluorocarbons, nitrous oxide, nitrogentrifluoride, methane, hydrofluorocarbons, HFEs, and carbon dioxide itself.

<sup>5</sup> Each emitted gas has a "global warming potential" defined in relation to carbon dioxide. For example, a pound of nitrous oxide (N<sub>2</sub>O) has a global warming potential of 298 times that of a pound of carbon dioxide.

2016 data on the EPA's Air Markets Division Web site<sup>6</sup> under a different set of facility identifiers. With the help of a master file of EPA identifiers, we can include the 2016 data, but as Figure 2, panel b, shows, this year has slightly less data. Removing the 2016 data does not change the direction or general magnitude of the results. We call the variables from the CAMD data *CO2C*, *SO2C*, and *NOC*.

We do not use the NEI data or the TRI data. NEI data are reported in pounds without adjustment for the toxicity of each substance, making aggregates difficult to interpret. Also, given our requirement for lagged data, only two waves of the NEI intersect with our data set: the 2011 and 2014 waves. The TRI also has no standardization for toxicity, and as Currie et al. (2015) and others point out, the data itself are of poor quality.<sup>7</sup>

Emission reports for a given firm year from the CAMD and the GHGRP are almost identical ( $\rho=0.98$ ) in the subset of 523 firm years where both are available. Differences arise in part because the GHGRP data provides one number of carbon dioxide equivalent emissions, whereas the CAMD data breaks down emissions into carbon dioxide, nitrogen oxides, and sulfur dioxides. In tests where power is desirable, we will use a combined variable that is equal to the CAMD estimate when this is available because this is the highest quality data, and the GHGRP estimate otherwise. Table 1 describes the construction of this variable.

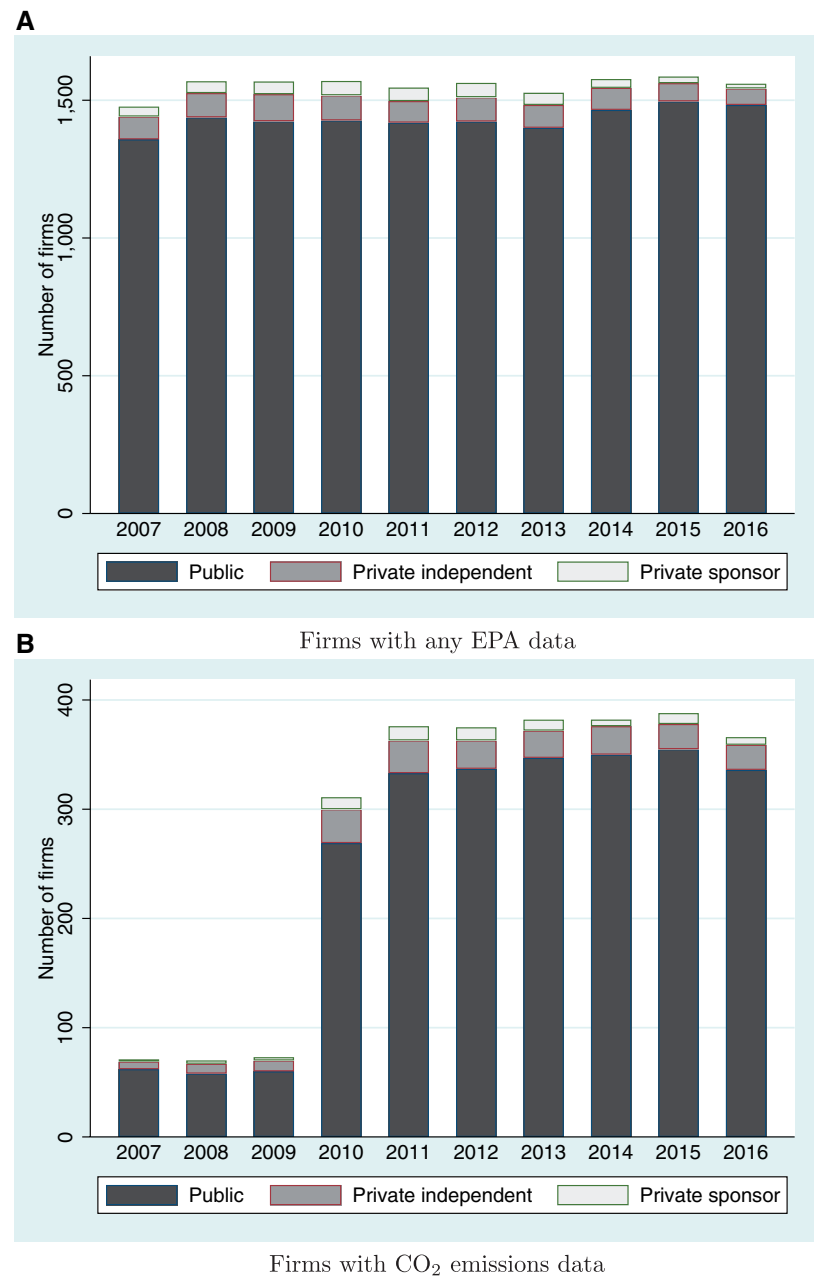
Figure 3 presents the emissions data by year for our sample of firms. Panels A and B present data from the GHGRP program, and Panels C and D present data from the CAMD. Emissions are in millions of metric tons of carbon dioxide equivalent. For an intuitive sense, 1 metric ton of CO<sub>2</sub> is emitted by driving one average passenger car for 2,445 miles, or by charging 127,512 smartphones according to the EPA's "Greenhouse Gas Equivalencies Calculator."<sup>8</sup> Panels A and C present raw emissions data, and Panels B and D present data scaled by the firm's revenues from Capital IQ. Although raw emissions slightly decrease, this trend is absent when emissions are scaled by revenues. Panels C and D also show that emissions of sulfur dioxide and nitrogen oxides are small in terms of CO<sub>2</sub>-equivalent compared to emissions of carbon dioxide. While these substances are toxic in other ways, they are not the principal causes of global warming at the levels at which the facilities in our data emit them.

Figure 4 presents the data by SIC code for the ten SIC codes with the highest averages in each data set. Not all SIC codes have firms with emissions data. The GHGRP program draws data from 131 SIC codes and the CAMD draws data from seventeen SIC codes. Like in Figure 3, Panels A and B present

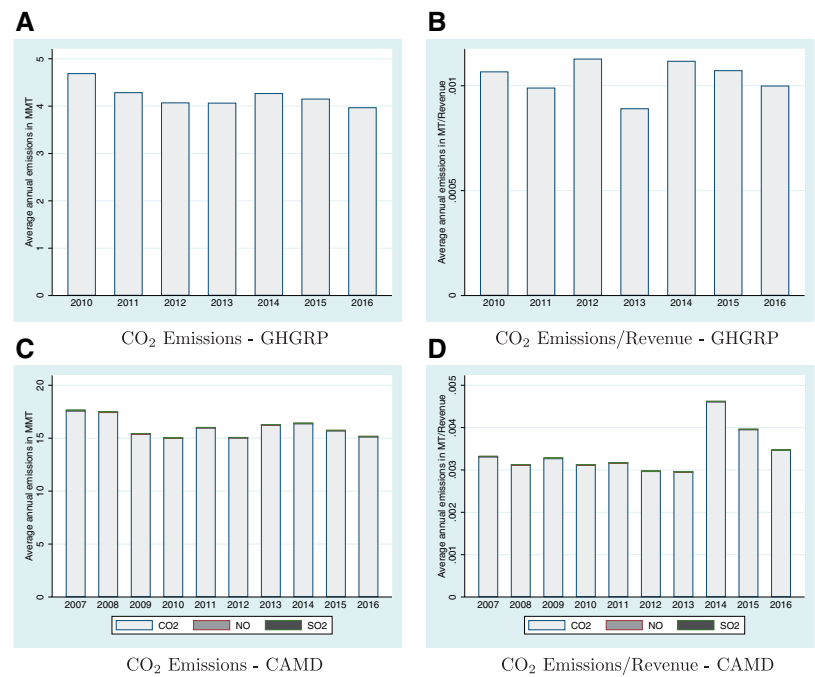
<sup>6</sup> [ampd.epa.gov](https://ampd.epa.gov)

<sup>7</sup> The EPA Web site warns that "While facilities must report chemical releases over a certain threshold, calculation methods are not prescriptive and there is a wide variation in accuracy of emissions reported under TRI." <https://echo.epa.gov/help/reports/air-pollutant-report-help> accessed on June 24, 2019.

<sup>8</sup> <https://www.epa.gov/energy/greenhouse-gas-equivalencies-calculator>



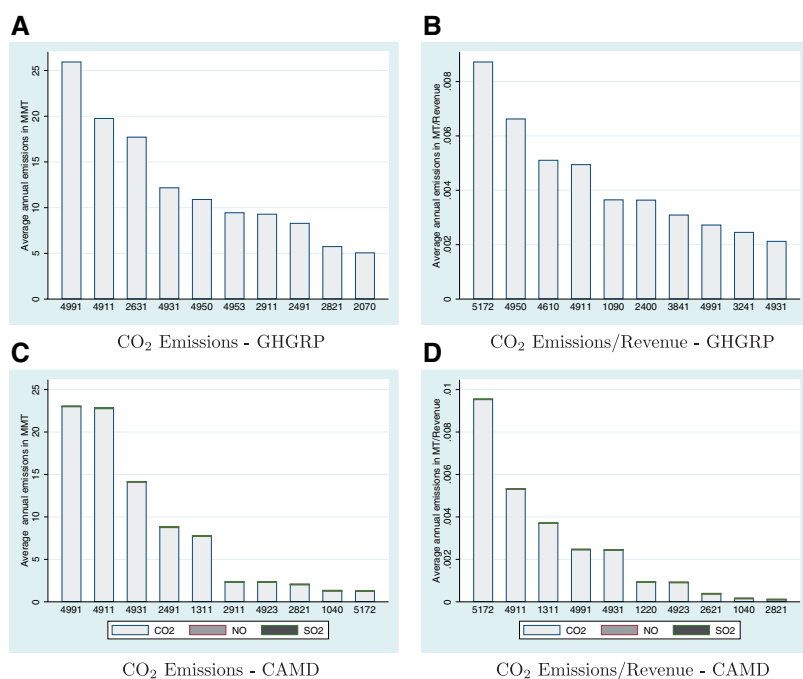
**Figure 2**  
**Firm types by year**  
Panel A presents the sample of firms that are monitored by the EPA. Panel B presents the subsample of firms that have CO<sub>2</sub> emissions data from either the GHGRP (2010-2016) or CAMD (2007-2015) emissions reporting programs



**Figure 3**  
**CO<sub>2</sub> equivalent emissions of greenhouse gases by year**  
Panels A and B present data from the GHGRP program and panels C and D present data from the CAMD. Emissions are in millions of metric tons of carbon dioxide equivalent for panels A and C, and in metric tons per dollar of revenue in panels B and D.

data from the GHGRP program, and Panels C and D present data from the CAMD. Panels A and C present raw emissions data, and Panels B and D present data scaled by revenues. Even within the top-ten industries, average annual greenhouse gas emissions varies greatly, and one challenge of the analysis will be to control for this variation. Lyubich, Shapiro, and Walker (2018) use proprietary data on plant-level fuel inputs to show that even within 6-digit NAICS industries (they use the production of carbon black as an illustrative example), the amount of energy used and the resultant amount of carbon dioxide emitted per unit of output vary greatly. These differences are driven by the cleanliness of the production technology and the energy inputs that the firms choose to use. Managers—even those within narrowly defined industries—have considerable leeway in their emission choices.

In addition to industry, we also include state fixed effects, as environmental regulations vary considerably by state. For example, deregulation of electricity markets was not uniform across states. Also, under the 2015 Clean Power Plan, the EPA assigned to each state a unique target and interim goals for emission reduction based on estimated feasibility, and allowed states to achieve

**Figure 4****CO<sub>2</sub> equivalent emissions of greenhouse gases by SIC code for the top 10 SIC codes**

Panels A and B present data from the GHGRP program and panels C and D present data from the CAMD. Emissions are in millions of metric tons of carbon dioxide equivalent.

reductions how they saw fit, and even to coordinate with other states to achieve the joint reductions. Target reductions ranged from zero reduction for Hawaii, Alaska, and Washington DC to over 40% for Illinois, Wisconsin, Minnesota, and others.

**1.2.2 Enforcement data.** Enforcement data are one measure of the severity that the EPA assigns to pollution by particular substances in particular locations. EPA enforcement data come from the Integrated Compliance Information System for Federal Civil Enforcement Case Data (ICIS FE&C). This data set contains information on informal and formal administrative cases and on judicial cases.<sup>9</sup> Administrative cases are those that take place before state or federal governing bodies, while judicial cases are those actions that take place in court, such as a breach of contract suit or other civil actions. State cases

<sup>9</sup> These cases fall under the Clean Air Act (CAA), the Clean Water Act (CWA), the Resource Conservation and Recovery Act (RCRA), the Emergency Planning and Community Right-to-Know Act (EPCRA) Section 313, the Toxic Substances Control Act (TSCA), the Federal Insecticide, Fungicide, and Rodenticide Act (FIFRA), the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA or Superfund), the Safe Drinking Water Act (SDWA), and the Marine Protection, Research, and Sanctuaries Act (MPRSA).

are available for some states, but not for others, requiring the use of state fixed effects in all our tests. For example, Consumers Energy, a subsidiary of CMS Energy, settled with the EPA in 2014 for modifying five of its coal-fired plants in such a way that caused releases of excess NO<sub>x</sub> and SO<sub>2</sub>. Although not admitting wrongdoing, Consumers Energy agreed to install technology to reduce the emissions and was required to spend at least \$7.7 million on environmental mitigation projects and to pay a \$2.75 million civil penalty.<sup>10</sup>

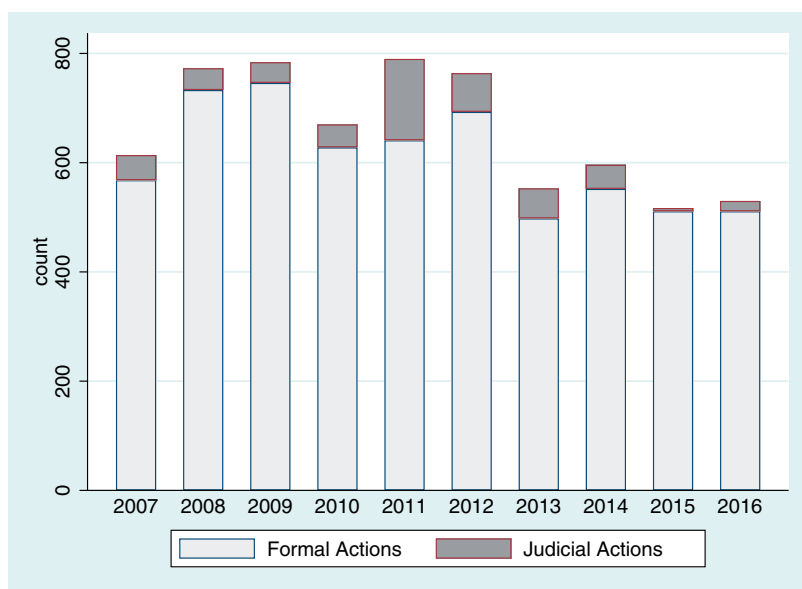
The enforcement data include general case information, information on which section of law was violated and over which periods, pollutants involved, the names of the defendants and the milestone dates of the case, and any penalty amounts. Penalty amounts are categorized as federal penalties, state and local penalties, Supplemental Environmental Project (SEP) costs, compliance action costs, and federal and state and local cost recovery amounts. SEP and complying action costs are estimates and are not paid directly to the EPA but incurred by the firm in order to clean up the pollution. Cost recovery amounts are incurred by the EPA in order to clean up the site and then billed to the responsible parties. We use total monetary outlay by the violator as an indicator of case severity, and we use the first date that the case was filed with the EPA to assign a year to the case. Table 2 presents summary statistics on the enforcement data at the firm level, and Online Appendix Table C1 presents the data at the facility level. These tables illustrate that enforcement actions are rare. Also, the enforcement data clearly contain far more firms than does the greenhouse gas emissions data set, because only a subset of firms is required to report emissions. Figure 5 presents formal and judicial actions by year. In this figure, it is apparent that the number of judicial actions has dropped off in recent years, whereas the number of formal actions has remained steady. Figure 6 presents the enforcement data for the top-ten SIC codes for various measures. Whereas SIC code 4931 (Electric and other services combined) has the highest average total penalty, SIC code 3390, Miscellaneous primary metal products, has the highest average penalty scaled by revenue.

## 2. Public and Private Firms and Greenhouse Gas Emissions

### 2.1 Choosing a dependent variable

Two broad approaches can be used in creating a dependent variable for this analysis. Although we are the first study in finance to our knowledge to use comprehensive data on greenhouse gas emissions, other studies have used related data and have faced this choice. Matsumura, Prakash, and Vera-Munoz (2014), Ben-David, Kleimeier, and Viehs (2018), and Ilhan, Sautner, and Vilkov (2019) use voluntary annual disclosure data from CDP, which covers roughly

<sup>10</sup> <https://www.epa.gov/enforcement/consumers-energy-clean-air-act-settlement>



**Figure 5**

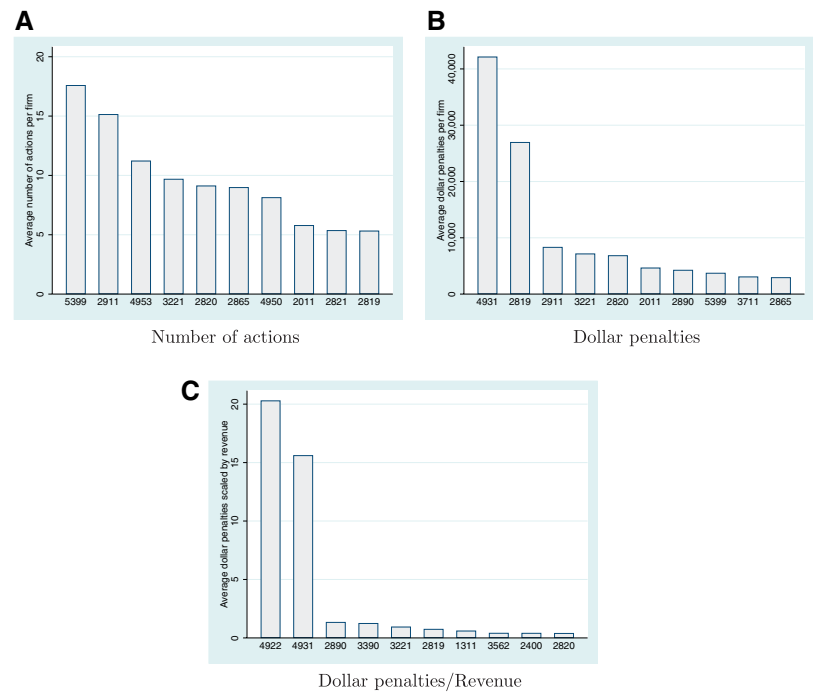
**Number of informal actions, formal actions, and judicial actions by year for our sample**

Formal actions and informal actions are resolved within the agency. Judicial actions are resolved by the courts.

half of S&P 500 firms. All three studies use the log of emissions as their dependent variable and control for size using the log of assets.

To add structure, one might instead scale emissions by a measure of output. The resultant “emission intensities” are commonly used for industrial production purposes when the measure of productive output that emissions are tied to is precise. Emissions intensities are highly variable across industries however, and we know of no study that uses emission intensities over different industries. Lyubich, Shapiro, and Walker (2018) infer CO<sub>2</sub> emissions from fuel consumption data for the year 2007 and examine variability of inverse emission intensities *within* 6-digit NAICS industries, but do not compare them across industries. In our study, we can only feasibly scale emissions by total firm revenues, with the further caveat that fiscal year revenues may not completely overlap with calendar year emissions.

No dependent variable is perfect, so we choose to calculate both. When we scale firms’ annual emissions by its *TotalRevenue* as a proxy for its annual output, we indicate this by using the extension *\_R* in the variable’s name. The ratios are highly skewed (skewness = 35 for *CO2eC\_R* in the firm-level data, for example), so we take their log, and the resultant variables are no longer skewed (skewness = -0.45 for *logCO2eC\_R* in the firm-level data). When the dependent variable is the log of emissions, we also control for the log of contemporaneous



**Figure 6**  
Number of actions and total penalties by SIC code for the top-ten SIC codes for each value  
Dollar penalties are in thousands, and revenue is in millions.

total revenue. Scaling or controlling for contemporaneous revenue assumes that firms do not choose to simply decrease their production in order to emit less.<sup>11</sup>

## 2.2 Summary statistics

Table 2 presents the summary statistics and the associated *t*-tests for differences between private firms and public firms. Raw measures of emissions are lower for private independent firms compared to public firms. For example, in the first line of the table, average annual emissions for the GHGRP program firms are 4.310 MMT (millions of metric tons) for public firms and 2.299 MMT for private independent firms. For large emitters in the CAMD program in the following row, average public firm emissions are 17.82 MMT for public firms and 5.048 MMT for private independent firms. These differences are significant in *t*-tests as indicated by the stars in the table. Values are more similar between private sponsor-backed firms and public firms. When we scale by revenues, we find the opposite relation: public firms emit less per dollar of revenue than private

<sup>11</sup> This seems to be true at least for airlines. See McCartney (2019).

independent firms, and this difference is significant in a  $t$ -test for GHGRP firms. Scaling by electricity generation yields inconclusive  $t$ -tests. Thus, it is not clear, without controlling for industry and other variables that are plausibly exogenous to the decision about how much to pollute, if corporate structure and emissions are related. Private independent firms make up 7.5% of the sample with any emissions data, but 12% of the sample with CAMD emissions data, indicating that private firms are more concentrated in heavy emissions industries. Also, private firms tend to use more leverage and are more asset intensive than public firms. All these characteristics may influence emissions.

### 2.3 Multivariate results

This subsection presents specifications that control for industry and other firm characteristics. Table 3 presents the regression results, with the unscaled dependent variable in panel A and the scaled dependent variable in panel B. Columns 1–4 of each panel examine CO<sub>2</sub>-equivalent emissions in metric tons at the firm level, and Columns 5–8 use the facility-level sample. Columns 1 and 5 present the CO<sub>2</sub> emissions from the broader GHGRP program, and Columns 2–4 and 6–8 present the CO<sub>2</sub> and CO<sub>2</sub>-equivalent emissions of NO<sub>x</sub> and SO<sub>2</sub> from the CAMD programs. We control for size,  $\log lagTotalAssets$ , the debt-to-asset ratio,  $lagDA$ , and capital intensity  $lagNetPPEA$ , the construction of which we describe in Table 1. For facility-level analyses, we divide firm level total revenue and total assets by the number of emitting facilities. Some dependent variables in the paper have limited or binary outcomes; however, to be able to include fixed effects, we still elect to use ordinary least squares (OLS) throughout the paper. We include fixed effects for 131 (17) 4-digit SIC codes and 38 (45) states for the GHGRP (CAMD) data sets, as well as for each of the years. We double-cluster the standard errors by year and by industry.

Coefficients in Table 3 suggest that private independent firms tend to emit less than their public counterparts. In the GHGRP data in Column 1, a private independent firm has log CO<sub>2</sub>-equivalent emissions that are 0.399 lower, which is 38% of the dependent variable's standard deviation of 1.042 from Table 2, Column 7. In terms of units of carbon emissions, private independent status is associated with a  $1 - \exp(-0.399) = 33\%$  decrease in the dependent variable from its geometric mean of 0.408 MMT of CO<sub>2</sub> equivalent (the arithmetic mean is 4.31 in Table 2, Column 1). For an intuitive sense, this 0.13 MMT of CO<sub>2</sub> is equivalent to the annual emissions of 27,601 passenger vehicles or 0.033 coal-fired power plants. In Column 2, for the large emitters in the CAMD program, emissions for private independent firms are 1.276 lower, which is 55% of the standard deviation of this variable (2.370 in Table 2, Column 7). In units of carbon emissions, this is a  $1 - \exp(-1.276) = 72\%$  decrease from the geometric mean of 3.56 (the arithmetic mean is 17.79 in Table 2), or 0.658 coal-fired power plants. This suggests that private independent firms emit less, especially in industries that have the highest emissions, that is, those covered by the CAMD program. Firms in less carbon-intensive industries are possibly

**Table 3**  
**Emissions**

Panel A

	(1) logCO2eG	(2) logCO2C	(3) logNOC	(4) logSO2C	(5) logCO2eG	(6) logCO2C	(7) logNOC	(8) logSO2C
PrivateIndependent	−0.399* (.08)	−1.276*** (.00)	−2.132*** (.00)	−4.585*** (.00)	−0.0808* (.09)	−1.477*** (.00)	−1.645*** (.00)	−2.465*** (.00)
PrivateSponsor	0.136 (.50)	0.610 (.51)	0.323 (.67)	0.622 (.59)	0.0426 (.49)	−0.400 (.32)	−0.0872 (.83)	0.182 (.77)
logTotalRevenue	0.182*** (.00)	0.831*** (.00)	0.775*** (.00)	0.836 (.12)	0.0165 (.25)	−0.0495 (.89)	0.0297 (.92)	0.685*** (.00)
lagDA	0.0225 (.88)	2.097*** (.00)	2.260*** (.00)	5.826*** (.00)	0.0297 (.30)	0.395 (.54)	0.107 (.91)	0.907 (.63)
loglagAssets	0.157** (.02)	0.232 (.47)	0.167 (.52)	0.229 (.65)	0.0204 (.34)	0.0648 (.84)	−0.0505 (.87)	−0.643** (.02)
lagNetPPEA	0.569 (.12)	1.940 (.31)	0.685 (.74)	−2.327 (.42)	0.0937 (.25)	−0.287 (.31)	−0.210 (.52)	−0.275 (.65)
Observations	2,579	732	736	689	18,132	5,411	5,539	4,481
R <sup>2</sup>	.686	.675	.719	.727	.243	.185	.251	.317
By	Firm	Firm	Firm	Firm	Facility	Facility	Facility	Facility
State FEs	YES	YES	YES	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES	YES	YES	YES
SIC4 FEs	YES	YES	YES	YES	YES	YES	YES	YES

Panel B

	(1) logCO2eG_R	(2) logCO2C_R	(3) logNOC_R	(4) logSO2C_R	(5) logCO2eG_R	(6) logCO2C_R	(7) logNOC_R	(8) logSO2C_R
PrivateIndependent	−0.588* (.09)	−1.294*** (.00)	−2.155*** (.00)	−4.609*** (.00)	−0.401*** (.01)	−1.511*** (.00)	−1.681*** (.00)	−2.501*** (.00)
PrivateSponsor	0.426 (.29)	0.656 (.48)	0.383 (.62)	0.665 (.57)	0.517** (.02)	0.130 (.61)	0.402 (.22)	0.320 (.58)
lagDA	0.0250 (.92)	2.133*** (.00)	2.304*** (.00)	5.867*** (.00)	0.0373 (.81)	0.733 (.41)	0.427 (.70)	1.036 (.59)
loglagAssets	−0.172** (.02)	0.0764 (.69)	−0.0408 (.72)	0.0770 (.53)	−0.766*** (.00)	−0.917*** (.00)	−0.964*** (.00)	−0.940*** (.00)
lagNetPPEA	1.389** (.04)	1.922 (.32)	0.654 (.75)	−2.360 (.41)	0.322 (.38)	−0.0541 (.76)	−0.0113 (.97)	−0.238 (.70)
Observations	2,579	732	736	689	18,132	5,411	5,540	4,482
R <sup>2</sup>	.711	.655	.725	.739	.452	.262	.317	.339
By	Firm	Firm	Firm	Firm	Facility	Facility	Facility	Facility
State FEs	YES	YES	YES	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES	YES	YES	YES
SIC4 FEs	YES	YES	YES	YES	YES	YES	YES	YES

Regressions of measures of reported emissions on measures of ownership. Table 1 defines the variables. In panel A, the dependent variables are unscaled emissions, and *logTotalRevenue* is included as a control variable. In panel B, emissions data are scaled by total revenue. In both panels, Columns 1 and 5 present GHGRP data, and the remaining columns present CAMD data. Columns 1–4 use firm-level data and columns 5–8 use facility-level data. Standard errors are clustered by industry and year, and *p*-values are in parentheses.

less careful about their emissions of greenhouse gases. Results are stronger for the CAMD data on NO<sub>x</sub> and SO<sub>2</sub>. Private independent firms have lower values of the dependent variable by 2.132, 82% of a standard deviation of NO<sub>x</sub>, and 4.585, 111% of a standard deviation of SO<sub>2</sub>.

Facility-level results in Columns 5–8 are similar. In Column 5, the coefficient on private independent firms is 0.0808, which is 16% of a standard deviation of the dependent variable (0.495 from Online Appendix C1). In terms of units of emissions, this is 7.8% drop from the geometric mean of 0.0978 MMT per facility, or 0.0076 MMT (the arithmetic mean of emissions per facility is 0.607 in Online Appendix Table C1). This is equivalent to the annual emissions of 1,614 cars or 0.002 coal-fired power plants. In the CAMD data in Column 6, private independent firms have emissions that are 1.477 lower which is 63% of a standard deviation of the dependent variable (2.340 from Online Appendix Table C1) and this represents a 77% drop from the geometric mean emissions per facility of 0.459 (the arithmetic mean is 2.26 from Online Appendix Table C1). This is equivalent to 75,038 cars or 0.091 coal-fired power plants.

Results are also similar in panel B using scaled dependent variables. For example, in Column 1 for GHGRP firms, emissions scaled by revenues are 0.588 lower, which is 26% of a standard deviation of the dependent variable, and for CAMD firms in Column 2, emissions are 1.294 lower, which is 56% of a standard deviation of the dependent variable. In these regressions, private sponsor-backed firms are rarely significantly different from public firms. This could be due to the smaller number of observations in sponsor-backed firms, but a look at the summary statistics confirms that mean values of variables tend to be closer to those of public firms. Thus, we find no evidence that private equity sponsors improve or worsen the prosocial behavior of their portfolio companies.

Some control variables are significantly associated with emissions as well. For the unscaled dependent variable in panel A, *logTotalRevenue* is significantly positively related to emissions, as expected. The relation between emissions and revenues is weak for the GHGRP data (0.182 in Column 1 of Table 3, panel A), possibly due to the large heterogeneity of relations between emissions and revenues in these industries. In this setting, a 1% increase in total revenue from the geometric mean of 22,384 for public firms is associated with an  $(1.01^{0.182} - 1) * 100 = 0.18\%$  increase in the dependent variable from its geometric mean of 0.408, or 734 MT of carbon dioxide emissions, which is equivalent to the annual emissions of 156 cars. This rather weak relation suggests that scaling by total revenue and forcing a one-to-one relation for such a broad panel of industries may not capture much of the variation in the dependent variable. The relation between revenue and emissions is stronger for the large emitters in the CAMD data, with coefficients of 0.831 and 0.775 in Columns 2 and 3. Using the coefficient in Column 2, a 1% increase in total revenue is associated with an  $(1.01^{0.831} - 1) * 100 = 0.83\%$  increase in the dependent variable from its geometric mean of 3.56, or 0.030 MMT of carbon

dioxide emissions, which is equivalent to the annual emissions of 6,273 cars or 0.008 coal-fired plants. This relation disappears for the facility-level results in Columns 5–8, possibly because our estimate of facility-level revenue, total revenue divided by the number of emitting facilities, is too imprecise.

The debt-to-asset ratio is also significantly related to emissions in Columns 2, 3, and 4 of Table 3, panel A, which presents the firm-level data from the CAMD. In Column 2, an increase of 0.01 in this ratio is associated with an increase in emissions of  $2.097 \times 0.01$ , which is 0.9% of the standard deviation of the dependent variable. In terms of emissions, this increase in the debt-to-asset ratio is associated with a  $\exp(0.10 \times 2.097) - 1 = 2.1\%$  increase from the geometric mean of 3.56, which is 0.0754 MMT, equivalent to the annual emissions of 16,016 cars or 0.02 coal-fired plants.

The ratio of property, plant and equipment to assets is related to emissions in these regressions in the GHGRP data with the scaled dependent variable. Size as measured by assets is generally negatively related to emissions for the scaled dependent variable, suggesting that, in that specification, there are economies of scale in emission reduction. For much of the remainder of the paper, we use the combined greenhouse gas emissions dependent variables *logCO2e* and *logCO2e\_R*, which use CAMD data when it is available, and GHGRP data otherwise. Including the firms with GHGRP data makes the results weaker but more reflective of the broader cross-section of firms rather than of large emitters. Columns 1 and 5 of Table 4, panels A and B, present these combined variables. The estimated coefficients are closest to those in Column 1 of Table 3, panels A and B, because the majority of the data come from the GHGRP.

Regressions in Table 3 include industry fixed effects, but it is possible that a level effect is not sufficient to capture all of the effects of variation across industries. A similar argument is made by Lerner and Seru (2017) regarding commonly used data on citations per patent, a variable that also varies greatly across industries. Their solution is to adjust citations per patent in each industry by the mean in that industry-year, and we do the same here. We require at least three observations in that industry-year in order to calculate the adjusted dependent variable, so this shrinks our sample somewhat. Columns 2 and 5 of Table 4 provides regression results when the dependent variable is adjusted by dividing by the mean within the industry and year, and results continue to be statistically and economically significant at the firm and facility levels.

Our results also could be driven by differences between the sample of private firms and that of public firms that may not be adequately captured by our fixed effects and control variables. For example, perhaps some public firm data outside the relevant range of the private firm observations could be driving the calculated coefficients. To address this possibility, we follow a matching approach. Each year, one public firm is matched to each private firm in the sample. The firms must be in the same 4-digit SIC code and we chose the closest

**Table 4**  
**Emissions**  
Panel A

	(1) logCO2e	(2) logadjCO2e	(3) logCO2e	(4) logCO2e	(5) logadjCO2e	(6) logCO2e
PrivateIndependent	-0.737** (.03)	-0.732** (.03)	-0.769** (.01)	-0.515** (.01)	-0.507** (.01)	-1.088*** (.00)
PrivateSponsor	0.255 (.58)	0.370 (.48)	0.561 (.36)	0.0210 (.84)	0.0202 (.84)	-0.190 (.43)
logTotalRevenue	0.584*** (.00)	0.625*** (.00)	1.435*** (.00)	0.109** (.02)	0.0994** (.03)	0.00248 (.99)
lagDA	0.0148 (.96)	0.00403 (.99)	0.160 (.63)	0.0266 (.79)	0.0382 (.64)	-0.116 (.52)
loglagAssets	0.215* (.05)	0.175 (.16)	-0.533*** (.00)	0.0912* (.05)	0.0957** (.04)	0.142 (.33)
lagNetPPEA	1.506** (.03)	1.454** (.05)	-0.637 (.43)	0.490 (.14)	0.452 (.17)	0.322 (.36)
Observations	2,794	2,125	465	19,828	19,356	1,755
R <sup>2</sup>	.703	.469	.778	.228	.160	.317
By	Firm	Firm	Firm	Facility	Facility	Facility
State FEs	YES	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES	YES
SIC4 FEs	YES	YES	YES	YES	YES	YES

Panel B

	(1) logCO2e_R	(2) logadjCO2e_R	(3) logCO2e_R	(4) logCO2e_R	(5) logadjCO2e_R	(6) logCO2e_R
PrivateIndependent	-0.809** (.01)	-0.738** (.02)	-0.685** (.02)	-0.934*** (.00)	-0.869*** (.00)	-1.230*** (.00)
PrivateSponsor	0.382 (.36)	0.580 (.23)	0.378 (.51)	-0.128 (.21)	0.0394 (.61)	-0.00905 (.98)
lagDA	0.00834 (.98)	-0.106 (.73)	0.115 (.72)	0.515 (.13)	0.408 (.21)	0.0690 (.79)
loglagAssets	-0.169** (.02)	-0.142* (.05)	-0.150 (.48)	-0.243*** (.00)	-0.218*** (.00)	-0.160 (.29)
lagNetPPEA	1.540** (.02)	1.490** (.03)	-0.524 (.50)	0.399 (.46)	0.655 (.16)	-0.286 (.65)
Observations	2,794	2,125	465	19,828	19,327	1,755
R <sup>2</sup>	.704	.231	.733	.410	.233	.364
By	Firm	Firm	Firm	Facility	Facility	Facility
State FEs	YES	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES	YES
SIC4 FEs	YES	YES	YES	YES	YES	YES

Regressions of measures of reported emissions on measures of ownership. Table 1 defines the variables. In panel A, the dependent variables are unscaled emissions, and *logTotalRevenue* is included as a control variable. In panel B, emissions data are scaled by total revenue. In both panels, Columns 1 and 4 present the combined emissions variable; Columns 2 and 5 present the adjusted dependent variable which divides by the mean from that industry-year, and Columns 3 and 6 present the matched sample. Columns 1–3 use firm-level data, and Columns 4–6 use facility-level data. Standard errors are clustered by industry and year, and *p*-values are in parentheses.

in total assets as the match. The matching is performed with replacement.<sup>12</sup> Columns 3 and 6 of Table 4 provides results, which are statistically and

<sup>12</sup> Maksimovic, Phillips, and Yang (2017) argue that matched public and private firms appear different, because they are at different stages in their life cycle and firms should be matched at the beginning of their lives and not contemporaneously. We do not have the data to perform this type of match.

economically significant in each case. It appears that the decrease in variance achieved by these normalizations compensates for the large loss of observations.

In untabulated regressions, we control for several other variables, none of which affect the results. We divide the debt-to-assets ratio into bank and nonbank debt and find a small positive association between bank debt and emissions and no association between nonbank debt and emissions. Similarly, a breakdown of secured versus unsecured debt finds that the former is generally positively related to emissions. We also create an indicator variable for utilities that are in locations and years where electricity prices are deregulated, and find that these utilities emit more, confirming findings in Fowlie (2010), but results are unaffected. We also use 2-digit rather than 4-digit SIC code fixed effects, and the Online Appendix Table C3 provides results, which are somewhat weaker. We insert firm fixed effects to identify the twenty-one firms with emissions data that switch between private and public, and we find generally statistically significant negative coefficients (Online Appendix, Table C5). We do not jump to conclusions, however, as the decision to switch from public to private entails many changes at the firm level. Lastly, in untabulated regressions, we control for characteristics of the location of the facility: distance (as the crow flies) from the closest EPA office, population density within a 3-mile radius, and the percentage of minority inhabitants within a 3-mile radius around the facility (see Online Appendix, Table C6). None of these specification changes significantly affect the results.

## 2.4 Subset of electric utilities

Next, we investigate electric utilities, a subset of our sample where one can control for electricity generation which is more closely related to emissions than revenue. The Energy Information Administration (EIA) provides electricity generation data in survey Form EIA-923<sup>13</sup> on all utilities in the United States at the generator level. These data also provide generator age, which may be a choice that utilities can make in order to regulate their emissions, and may be relatively fixed in the short term because of the high cost of upgrading equipment. We match the data to the emissions data at the facility level using identifiers provided by the EIA. We aggregate electricity generation in megawatt hours (MWH) and generator age in years up to the facility level, weighting each generator's age by its annual electricity output. We also aggregate these values up to the firm level, weighting age by generation. The dependent variable in Table 5, Columns 1–4, is the log of the entity's CO<sub>2</sub> output, and in Columns 5–8 emissions are scaled by annual electricity generation. We call the scaled variable *logCO2e\_GEN*. Like those in prior tables, these regressions include the usual control variables, state, year and 4-digit SIC fixed effects.

Like in the earlier analysis, we find a negative relation between emissions and the indicator for private independent firms. In Column 1, a private independent

<sup>13</sup> The data are available at <https://www.eia.gov/electricity/data/eia923/> (page 1, Generation and Fuel Data).

**Table 5**  
**Emissions scaled by electricity generation for utilities**

	(1) logCO2e	(2) logCO2e	(3) logCO2e	(4) logCO2e	(5) logCO2e_GEN	(6) logCO2e_GEN	(7) logCO2e_GEN	(8) logCO2e_GEN
PrivateIndependent	−0.187* (.10)	−0.0952* (.09)	−0.271*** (.01)	−0.170*** (.01)	−0.188** (.03)	−0.0792 (.13)	−0.235** (.03)	−0.125* (.06)
PrivateSponsor	−0.0533 (.32)	0.0339 (.62)	−0.0287 (.78)	−0.0639 (.27)	−0.0540 (.28)	0.0380 (.53)	−0.0165 (.87)	−0.0469 (.43)
logNetGeneration	1.001*** (.00)	0.976*** (.00)	0.973*** (.00)	0.961*** (.00)				
logPlantAge		0.269*** (.00)		0.271*** (.00)		0.250*** (.00)		0.257*** (.00)
Observations	738	738	5,315	5,272	738	738	5,315	5,272
R <sup>2</sup>	.984	.987	.932	.940	.465	.540	.130	.218
By	Firm	Firm	Facility	Facility	Firm	Firm	Facility	Facility
Controls	YES	YES	YES	YES	YES	YES	YES	YES
State FEs	YES	YES	YES	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES	YES	YES	YES
SIC4 FEs	YES	YES	YES	YES	YES	YES	YES	YES

Columns 1–4 present unscaled emissions, and Columns 5–8 present emissions scaled by electricity generation, from Form EIA-923, Part 1. Control variables not shown are *loglagTotalAssets*, *lagDA*, and *lagNetPPEA*. Table 1 defines the variables. Columns 1, 2, 5 and 6 present firm-level data, and Columns 3, 4, 7, and 8 present facility-level data. Standard errors are clustered by industry and year, and *p*-values are in parentheses.

firm has log of emissions that are 0.187 lower than comparable publicly traded utilities, which is 8% of the standard deviation of the dependent variable (2.33). In units of emissions, switching from a public firm to a private independent firm is associated with emissions that are lower by 21% at the geometric mean of the dependent variable, which is 0.498. This amounts to 0.104 MMT of CO<sub>2</sub>, which is the annual emissions of 22,204 cars or 0.027 coal-fired power plants. The coefficient halves when controlling for the weighted average age of the facility's generators. Not surprisingly, *logPlantAge* is significantly related to emissions. Increasing plant age by 10 years raises the log of plant age by 0.325 and using the coefficient of 0.269 in Column 2 of Table 5, this is associated with an increase in log emissions of 0.087, or 3.7% of a standard deviation of the dependent variable. In terms of units of emissions, 10 years represents 47% of the geometric mean of weighted generator age for public firms. Raising generator age by this amount is associated with an increase in emissions of  $(1.47^{0.269} - 1) * 100 = 10.91\%$ . From the geometric mean of 0.498, this is 0.054 MMT of CO<sub>2</sub>, which is equivalent to annual emissions from 11,535 cars or 0.014 coal-fired plants. In untabulated results, we find that private independent utilities have a weighted average generator age of 24.0 years compared to 26.8 years for public firms, but we cannot say whether this is a choice that is made in part to reduce emissions.

Electricity generation is also statistically and economically related to emissions. The coefficients in Columns 1–4 of Table 5 are close to 1, so a 1% increase in revenues is associated with a 1% increase in the dependent variable. This seems to justify scaling emissions by electricity generation as we do in Columns 5–8. In these columns, we find that the indicator for a private independent firm is associated with a decrease in scaled emissions of 0.188 in Column 5, which is 47% of a standard deviation of the dependent variable. Note that we expect this result to be stronger in units of standard deviation than for the unscaled dependent variable, as we have taken out much of the variation in the dependent variable by scaling by output. Like in Columns 2 and 4, the size of the effect decreases by half when controlling for weighted generator age and is not statistically significant at the firm level in Column 6 but is statistically significant at the facility level in Column 8.

### 3. EPA Actions and Fines

Next, we examine EPA actions and penalties. Dependent variables include the number of formal and judicial actions per firm-year or facility-year and the log of one plus the total dollar penalty assigned. Using OLS allows us to include fixed effects and guarantee convergence, even though the first three dependent variables are count variables and the fourth is strictly positive. Table 6 shows that actions and penalties are generally lower for independent private firms. For example, in Column 1 of panel A, for private independent firms the coefficient on the number of formal actions is -0.227, and the standard deviation of the

dependent variable is 2.229 so this is a 10%-of-a-standard deviation effect. In Table 6, panel B, we examine an adjusted dependent variable by scaling by the annual industry average value as recommended by Lerner and Seru (2017). Here, we find at the firm level that private independent firms have fewer judicial actions, and at the facility level that they have fewer formal administrative actions, judicial actions, and lower penalties scaled by average facility revenue. Table 6, panel C, examines a matched sample. In this table, results are only statistically significant for the most serious judicial actions, possibly because of the lower number of observations.

#### 4. Potential Drivers of Differential Emissions

This section explores potential drivers of the differences that we find between public and private firms. Our strategy is to use the rich data that is available for public firms to explore the variation in emissions among public firms, and use these insights and our knowledge of the governance differences between public and private independent firms to craft an educated guess about the drivers of the difference in emissions among public and private firms.

In these analyses, we use the combined emissions variable that uses both GHGRP and CAMD data, and we examine only firm-level data because all explanatory variables of interest are at the firm level. We leave emissions unscaled, while controlling for the log of revenues like in prior tables. Tests using the scaled dependent variable produce very similar conclusions.

##### 4.1 Transparency

We first test whether disclosure requirements and other drivers of transparency affect firms' decisions as reputation effects may be heightened if the public is aware of a corporate leader's decisions. Some evidence in the literature suggests that this may be the case. Karpoff, Lott, and Wehrly (2005) uncover reputational penalties for polluting, and Duflo et al. (2013) find that transparency in the environmental auditing process decreases pollution among Indian firms. We use three measures of exposure to the public eye. The first measure is the log of the firm's age, which we compute using the founding and IPO dates from Jay Ritter's Web site.<sup>14</sup> We construct this as the year minus the founding date if it is available, or the year minus the IPO date otherwise. We hypothesize that older firms are more familiar to the public and have a more valuable reputation. Age also could be a measure of how technologically innovative a firm is, however, with younger firms potentially being more innovative and polluting less, so it is unclear which way the relation should go. Table 7, Column 1, shows that firm age is not significantly related to emissions. Next, we use our hand collected data on whether each firm files a 10-K on EDGAR in a given year. Although

<sup>14</sup> [https://site.warrington.ufl.edu/ritter/ipo-data\[MOU9\]/](https://site.warrington.ufl.edu/ritter/ipo-data[MOU9]/)

**Table 6**  
**Actions and penalties**

Panel A						
	(1) numAFR	(2) numJDC	(3) logTotalPenalty	(4) numAFR	(5) numJDC	(6) logTotalPenalty
PrivateIndependent	-0.227* (.05)	-0.0264** (.05)	-0.251* (.08)	-0.0209 (.12)	-0.00227* (.05)	-0.0574** (.03)
PrivateSponsor	0.0232 (.90)	-0.0269* (.09)	-0.00473 (.95)	0.0142 (.49)	-0.000865 (.40)	0.0111 (.70)
logTotalRevenue	0.124 (.13)	0.00270 (.66)	0.112** (.02)	-0.00655*** (.00)	-0.000611*** (.00)	-0.00682*** (.00)
lagDA	-0.189 (.14)	-0.00666 (.34)	-0.0455 (.37)	-0.0108 (.35)	-0.00126 (.15)	-0.0156 (.42)
loglagAssets	0.129* (.09)	0.00826 (.26)	0.0713** (.04)	-0.00617 (.25)	-0.000680 (.25)	-0.0165 (.14)
lagNetPPEA	-0.144 (.64)	-0.0146 (.39)	-0.104 (.61)	-0.0254 (.44)	-0.000260 (.91)	-0.0502 (.38)
Observations	13,186	13,186	13,186	217,373	217,373	217,373
R <sup>2</sup>	.218	.136	.261	.014	.007	.016
By	Firm	Firm	Firm	Facility	Facility	Facility
State FEs	YES	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES	YES
SIC FEs	YES	YES	YES	YES	YES	YES
Panel B						
	(1) adjnumAFR	(2) adjnumJDC	(3) logTotalPenalty	(4) adjnumAFR	(5) adjnumJDC	(6) logadjTotalPenalty
PrivateIndependent	-0.0823 (.66)	-0.675 (.15)	-0.251* (.08)	-0.646 (.48)	-2.691 (.22)	-0.0420** (.02)
PrivateSponsor	-0.0283 (.92)	-0.219 (.64)	-0.00473 (.95)	0.401 (.69)	0.529 (.71)	0.0320 (.29)
logTotalRevenue	0.276*** (.00)	0.573*** (.01)	0.112** (.02)	-0.535** (.01)	-0.221 (.28)	-0.00543*** (.01)
lagDA	-0.0733 (.72)	-0.546 (.16)	-0.0455 (.37)	-1.064 (.23)	-2.462** (.05)	-0.0312** (.04)
loglagAssets	0.377*** (.00)	0.0894 (.73)	0.0713** (.04)	-0.507 (.26)	-1.411 (.22)	-0.0143 (.11)
lagNetPPEA	0.201 (.71)	-1.628* (.05)	-0.104 (.61)	-3.150 (.18)	-9.343*** (.01)	-0.0462 (.29)
Observations	7,491	2,059	13,186	203,214	108,517	201,069
R <sup>2</sup>	.105	.063	.261	.005	.002	.013
By	Firm	Firm	Firm	Facility	Facility	Facility
State FEs	YES	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES	YES
SIC FEs	YES	YES	YES	YES	YES	YES
Panel C						
	(1) numAFR	(2) numJDC	(3) logTotalPenalty	(4) numAFR	(5) numJDC	(6) logTotalPenalty
PrivateIndependent	0.0183 (.83)	-0.0272** (.03)	-0.0139 (.88)	-0.0136 (.26)	-0.00184 (.19)	-0.0315 (.11)
PrivateSponsor	0.254 (.32)	-0.0327* (.08)	0.143 (.25)	0.0148 (.32)	0.00174 (.20)	0.0209 (.10)
logTotalRevenue	0.0123 (.86)	0.0110* (.09)	0.0484 (.41)	-0.00581 (.43)	-0.000366 (.53)	-0.00304 (.79)
lagDA	0.0812** (.05)	0.00205 (.75)	0.113 (.13)	-0.0132 (.10)	-0.00219 (.29)	-0.00758 (.73)
loglagAssets	0.136 (.16)	-0.00515 (.51)	0.107 (.11)	-0.00532 (.30)	-0.000978 (.29)	-0.00335 (.62)
lagNetPPEA	-0.0987 (.66)	0.0264 (.51)	0.430 (.12)	0.0309 (.30)	0.00456 (.24)	0.135** (.03)
Observations	1,577	1,577	1,577	10,251	10,251	10,251
R <sup>2</sup>	.401	.221	.305	.064	.060	.052
By	Firm	Firm	Firm	Facility	Facility	Facility
State FEs	YES	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES	YES
SIC FEs	YES	YES	YES	YES	YES	YES

Regressions of measures of EPA enforcement activity on measures of ownership. Table 1 defines the variables. Panel A presents the original data; panel B presents an adjusted sample; and panel C presents a matched sample. In all panels, Columns 1–4 present firm-level data and Columns 5–8 present facility-level data. Standard errors are clustered by industry and year, and *p*-values are in parentheses.

**Table 7**  
**Correlates of emissions**

	(1) logCO2e	(2) logCO2e	(3) logCO2e	(4) logCO2e	(5) logCO2e	(6) logCO2e	(7) logCO2e	(8) logCO2e	(9) logCO2e	(10) logCO2e
logAge	0.0136 (.90)									
Edgar10K		0.812* (.06)								
logCountGreenhouseGas			0.0998** (.04)							0.0752 (.34)
Maxinstown				−0.451 (.24)						−4.153** (.04)
ActiveMFown					−0.790** (.04)					−0.589 (.40)
PassiveMFown					−2.185 (.16)					−7.566** (.04)
Boardsize						−0.0747** (.02)				−0.0939** (.02)
ERC_suedecile							16.05*** (.00)			22.01 (.27)
GParachute								0.378** (.03)		0.394* (.09)
CBoard									−0.0775 (.68)	−0.0525 (.76)
Observations	912	287	2,336	2,358	2,325	1,507	2,344	1,562	1,562	1,303
R <sup>2</sup>	.778	.864	.715	.738	.747	.803	.739	.802	.800	.829
By	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
SIC4 FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

The dependent variable is the log of emissions scaled by revenues. Column 2 uses only private firms, whereas in the other columns, data are only available for public firms. Control variables not shown are *logTotalRevenue*, *loglagTotalAssets*, *lagDA*, and *lagNetPPEA*. Table 1 defines the variables. Standard errors are clustered by industry and year, and *p*-values are in parentheses.

no specific SEC disclosure requirements are related to carbon emissions, any material information must be disclosed in a 10-K. Materiality of climate change-related information is discussed in the SEC's Commission's interpretive release entitled *Guidance Regarding Disclosure Related to Climate Change*.<sup>15</sup> In this regression, we use only private firms because all public firms in our sample file 10-Ks. Table 7, Column 2, shows that a 10-K filing requirement among private firms is associated with higher (not lower) emissions. Private firms that file a 10-K have emissions that are  $(\exp(0.812) - 1) * 100 = 125\%$  higher at the geometric mean of 0.35 among these 287 observations. This amounts to 0.4375 MMT, or the annual emissions of 92,887 cars, or 0.11 coal-fired power plant. To further explore the possibility that public attention affects emissions choices, we create variables measuring the presence in the 10-K (for 10-K filers only) of language related to climate change. We believe that firms are unlikely to insert spurious language about climate change in their disclosures because the SEC's *Guidance Regarding Disclosure Related to Climate Change* states that registrants should "avoid generic risk factor disclosure that could apply to any company" (p. 22).

Using the SEC suite in WRDS, we count matches to the string "climate change" or the string "greenhouse gas" in 10-Ks in each year during our sample period. According to the SEC interpretive release, discussion of climate change could be appropriate in the Description of business, Legal proceedings, Risk factors, and/or Management's discussion and analysis (MDA) sections of the 10-K. From reading through the instances where these words appear, in most cases the words are used in the discussion of existing or potential future regulation of greenhouse gases that might affect the company. We create an indicator variable for the presence for each of these words in the 10-K and also variables that are the log of 1+ the number of times each string appears in the 10-K. Among firms that file 10-Ks, the correlation among the two indicator variables is 0.69 and the correlation in the log count variables is 0.49.

As Table 7, Column 3, shows the log of the count of instances of "greenhouse gas" is positively related to the dependent variable of greenhouse gas emissions per dollar of revenue, controlling for the usual control variables and fixed effects. The indicator variable for the presence of the word in the 10-K produces a similar result and is not shown. The indicator for the presence, or the count of the instances of string "climate change" are not related to the dependent variable and remain untabulated. For a sense of the economic size of the coefficient on *logCountGreenhouseGas*, one extra instance of the word in the 10-K, which is a 23% increase over the geometric mean of 4.33, is associated with an  $(1.23^{0.0998} - 1) * 100 = 2.09\%$  increase in emissions, which at the geometric mean in these data of 0.444, is 9,280 MT - the emissions of 1,970 passenger cars annually.

<sup>15</sup> SEC (2010): <https://www.sec.gov/rules/interp/2010/33-9106.pdf>. Washington, DC: The Securities and Exchange Commission (SEC).

Our interpretation of this result is that firms with risk factors related to their carbon emissions are rightly flagging these in their 10-Ks, and, hence, the direction of causality is from the emissions to the flagging. We conclude that we find no evidence that reputation effects of age, or transparency regarding carbon emissions that is either forced (the firm must file a 10-K) or slightly more discretionary (discussing emissions as a risk factor) are associated with lower emissions, controlling for industry, year, and other control variables.

## 4.2 Personal responsibility

To test the hypothesis of Hart and Zingales (2017) that personal responsibility for corporate decisions caused by concentrated power, as opposed to amoral drift caused by diffuse ownership, will drive more prosocial behavior, we examine variables that are related to how much personal responsibility corporate decision-makers—the CEO or a large influential investor—are likely to feel. Private firms tend to have more concentrated power, so a finding here could shed light on why private firms tend to pollute less than do comparable public firms. Although our prior finding that sponsor-backed firms pollute like public firms does not support the hypothesis that concentrated power itself leads firms to pollute less, perhaps personal responsibility plays a role in reducing pollution.

We first consider an indicator variable for whether the CEO is also the chairperson of the board, which we obtain from the IRRC directors database. We expect this measure to be negatively related to emissions if concentrated power induces the CEO to feel more personally responsible, but we find no relation and this regression remains untabulated. Edmans (2009) shows that blockholders manage to influence the firm to pursue long-term goals through threatening to vote with their feet, so we consider variables measuring concentration of power at the large investor level. *Maxinstown* is the ownership percentage of the largest institutional investor. Table 2, panel B, shows that this variable has a mean of 9% in public firms with emissions data. Although this variable is not statistically significantly related to emissions in Column 4, controlling for other variables like mutual fund ownership in Column 10, it is significantly negatively related to emissions.

We also construct the proportion of mutual fund ownership using the CRSP mutual fund database, as mutual funds are in a position to demand governance changes in the firms they invest in. We divide this variable into *ActiveMFown* and *PassiveMFown*, where passive mutual fund ownership is all ownership by mutual funds with any index fund indicator, combined with exchange traded funds (not exchange-traded notes). We call the remainder of funds active funds. Table 2, panel B, shows that active ownership averages 15%, whereas passive ownership averages 10.2% of shares in our sample of firms with emissions data. Table 7, Column 5, shows that active ownership is associated with lower emissions, while passive ownership is not significantly related to emissions. A 1-percentage-point increase in active ownership is associated

with an  $(\exp(-0.790 \times 0.01) - 1) \times 100 = 0.79\%$  decrease in emissions at the geometric mean in this sample of 0.472, or 3,720 MT, which is the equivalent of 790 passenger cars. When including all independent variables in Column 10, however, we find that passive ownership is significantly negatively related to emissions, whereas active ownership is not. In that regression, a 1-percentage-point increase in passive ownership is associated with a 7.28% drop in emissions from its geometric mean. This sample is much smaller, however, because of the requirement that all of these additional variables are defined. In untabulated results, mutual fund ownership in aggregate is significantly negatively related to emissions in both specifications, with a coefficient of approximately 1.11. Using this coefficient for total mutual fund ownership in this specification, we would find that a 10-percentage-point increase in mutual fund ownership is associated with a  $(\exp(-1.11 \times 0.1) - 1) \times 100 = 10.5\%$  drop in emissions, which at the geometric mean would represent 49,560 MT or the equivalent of the annual emissions of 10,522 passenger cars. This is approximately 38% of the difference we find between public and private independent firms in Table 3. We conclude that either mutual funds prefer to invest in companies that emit less, or that mutual fund managers pressure their portfolio companies to some extent. This result is consistent with findings by Dyck et al. (2019), who find that institutional investors positively influence ESG in the firms they hold.

Lastly, we consider the potential effect of boards, who are selected by investors. Members of a smaller board may feel greater personal responsibility to act in environmentally sound ways. We find the opposite. The variable *Boardsize* averages 10.5 in Table 2, panel B. An additional board member is associated with emissions that are 7.19% lower at their geometric mean of 0.668 in that sample. This is 48,096 MT, or the equivalent of 10,211 passenger cars. This is roughly one-third of the difference associated with the private independent firm indicator in Table 3. We hypothesize that this variable may, in fact, be a measure of whether the board has a specific committee or member responsible for environmental matters and who can thus devote attention to them.

Thus, we find some support for the personal responsibility of large investors affecting emissions decisions, but no support for the personal responsibility of CEOs or board chairs in these decisions. How might this shed light on the differing rates of pollution among public and private firms? Like the managers of private firms, large investors of public firms may feel that their reputation is at stake, because their holdings are most often publicly disclosed, and they cannot sell their holdings quickly without incurring significant liquidity penalties. For this same reason, they might be the most desirous to maximize long-term value and reduce the long-term risks associated with pollution. In contrast, smaller investors, CEOs of public companies, and private equity managers may have a shorter

horizon. We investigate specific measures of short-term pressure in the next section.

### 4.3 Short-termism

We now turn to the possibility that investor short-termism causes firms to pollute more, as suggested in Hart and Zingales (2017). The first variable that we examine is the earnings response coefficient. This is the coefficient from a regression of firm-level excess returns over the CRSP value-weighted market portfolio on the earnings announcement date on unexpected portion of companies' earnings announcements, measured by standardized unexpected earnings, or SUE. This variable has a long history (see, e.g., Collins and Kothari 1989). We use the decile that this coefficient falls in because Mendenhall (2004) shows that this is more linearly related to returns than the coefficient itself. Table 7, Column 7, shows that this variable is positively related to emissions as one might expect, but this relation disappears in Column 10 when the other variables are included.

We also include *GParachute*, which is an indicator for whether the firm has a golden parachute, *CBoard*, indicating that the firm has a staggered board. In Table 2, panel B, 83% of firms with emissions data have golden parachutes, whereas 32% have staggered boards. In untabulated results, an indicator variable for whether the firm has a poison pill is unrelated to emissions. These features make it more difficult for top decision-makers at the firm to be quickly replaced in the event of poor short-term financial performance. We find that the presence of a golden parachute is positively related to emissions. A firm with a golden parachute is associated with emissions that are 45% higher relative to the geometric mean which is 0.676 in that sample. This is equivalent to 310,284 MT, or 65,878 passenger cars. The other two variables are unrelated to emissions. This provides at best partial support for the hypothesis that pressure to perform in the short term is associated with more pollution.

## 5. Conclusion

In a hand-matched sample of EPA facilities and Capital IQ firms, we find evidence that private firms have lower greenhouse gas emissions than do comparable public firms, and that private firms incur fewer and lower EPA fines in some specifications. Hypothesizing that private firms have more concentrated ownership and less investor pressure for short-term financial performance, we investigate whether variables proxying for these effects among public firms drive differences in emissions among these firms. We find some evidence in favor of concentrated ownership and personal responsibility and mixed evidence in favor of short-term investor pressure driving these results. Among the many possible explanations that we cannot test using these data, personal experiences and beliefs of managers may play a large role in their decisions about emissions and may be a promising avenue for future research.

A question that arises is whether these results can inform policy decisions in the United States and in other countries. Let us first consider the energy sector, as it is the biggest producer of greenhouse gases in our data. In the United States, the energy sector includes publicly traded firms that are often master limited partnerships, and private utilities are often cooperatives. In Europe, firms tend to be larger and governments tend to have greater involvement, and in China, the state has even stronger involvement in the energy sector. In these situations, the state could potentially exert pressure in the same way that mutual funds appear to in our data. A common theme in U.S., European, and Chinese energy sectors in the last three decades has been the separation of generation and transmission of energy into separate corporate entities. In the United States, private generation cooperatives that are owned by customers partially recreate the vertical integration that existed in the past. Perhaps, vertical integration creates more personal responsibility because producers, transmitters and end-users cannot pin the blame on one another as they can when they are separate entities. Clearly, we see the benefits of separation for competitive reasons, and there may be better ways to assign personal responsibility, however, so we stop short of recommending reintegration without further study. Beyond the energy sector, we can say that the variables that seem to drive differences in emissions among public firms (mutual fund ownership and probable oversight, better board oversight), and that we hypothesize drive the differences among public and private firms, can carry over to an international setting. For example, European large investors are at an advanced stage of Environmental, Social and Governance (ESG) adoption.<sup>16</sup> Furthermore, some countries, like Germany, require boards to include members who are representatives of stakeholders other than shareholders. These measures may result in firms better internalizing the externalities that they create.

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<sup>16</sup> See Schrodgers (2017).

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